# A Statistical Assessment of Work-from-home Participation During Different Stages of the COVID-19 Pandemic

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## SHORT SUMMARY

Responses to the COVID-19 pandemic have dramatically transformed industry, healthcare, mobility, and education. Many workers have been forced to shift to work-from-home, adjust their commute patterns, and/or adopt new behaviors. This paper focuses on two major shifts along different stages of the pandemic. First, it investigates switching to work-from-home during the pandemic, followed by assessing the likelihood of continuing to work-from-home as opposed to returning to the workplace. Using a survey collected in July and August of 2020 in the U.S., it is found that nearly 50 percent of the respondents who did not work-from-home before but started to work-from-home during the COVID-19 pandemic, indicated the willingness to continue work-from-home. The methodological approach used to study work-from-home probabilities in this paper captures the complexities of human behavior by estimating two random parameters logit models with heterogeneity in the means and variances of random parameters.

**Keywords:** travel behavior and COVID-19, telecommute, random parameters model with heterogeneity in the means, work-from-home

## 1. INTRODUCTION

COVID-19 has forced many workers to adapt to new behaviors, norms as well as shifted commute patterns, preferences and mandated many to work-from-home. Despite many abrupt changes to daily routines and commutes that happened mostly in the earlier months of the COVID-19 pandemic, a significant share of workers continued to work-from-home as employers and organizations were constantly encouraging this pattern to combat the spread of infections and ensure the health and safety of the employees.

Preliminary research in this domain has shown that, although a significant share of the working population is likely to go back to in-person pre-COVID work arrangements, there does remain the possibility that a substantial number of workers would continue to work-from-home (Menon et al., 2020). While most workers have shifted to remote work since the onset of the pandemic, the post-pandemic working paradigm is not yet known.

A key element in the behavioral response to the pandemic has been to work-from-home that has been enabled largely by web technologies (Sakellariou et al., 2021). Historically, there has been extensive research on work-from-home adoption and frequency from a choice modeling perspective. In general terms, probabilities of working from home were found to be a consequence of multiple factors, including demographic, occupational, and attitudinal (Yen and Mahmassani, 1984), and investigations have been conducted through stated preference (Sullivan et al., 1993; Mokhtarian and Salomon, 1994; Mannering and Mokhtarian, 1995) and revealed preference surveys (Popuri and Bhat, 2003). While the traditional work-from-home/telecommuting literature has provided valuable insights into underlying behaviors, it is worth noting that the current wave of telecommuting, with the onset of COVID-19, has been motivated by necessity as opposed to the evolution of travel/activity behavior.

Early studies from the United States indicated a high percentage of teleworkers and virtual services in response to the COVID-19 pandemic (Menon et al., 2020). When asked about their behavior when COVID-19 would no longer be a threat, approximately 90 percent of respondents from a panel study on the mobility of Dutch workers anticipated an increase in out-of-home activities, whereas 27 percent of workers planned to continue working from home (de Haas et al., 2020). The overall impact of telework on reducing travel demand, decreasing congestion, and increasing the use of active transportation modes has been documented by several early-stage studies (Elldér, 2020).

In the current study, the starting point is the pre-pandemic stage and particularly the workers who did not work-from-home. Next, the switch to work-from-home is investigated (Table 2). Once the workers have switched to work-from-home either willingly or by necessity, a conditional model on the willingness to continue to work-from-home after the pandemic is estimated (Table 2). The main objective is to study factors determining the individuals' willingness to continue to work-from-home and/or return to the workplace after they experience work-from-home during the pandemic (please see Figure 1 for conceptual diagram of the study). The framework of accounting for initial states and developing subsequent models that were consequences of prior states was also employed by Sheela and Mannering (2020).

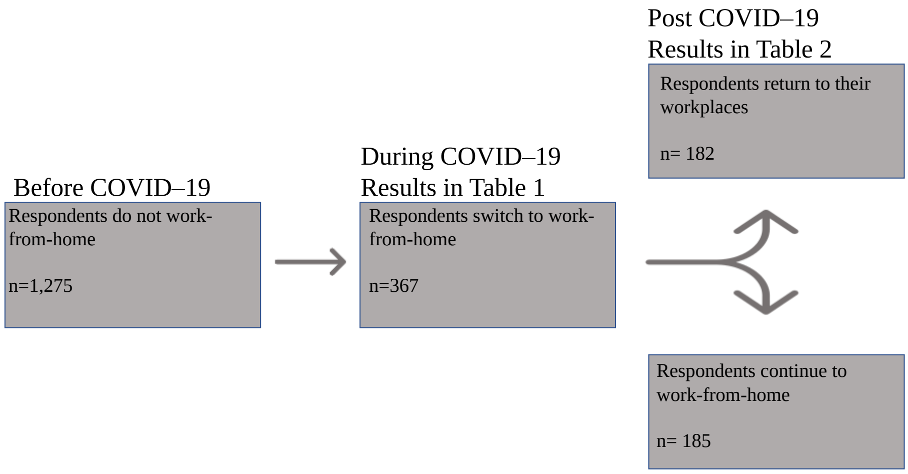


**Figure 1. Conceptual framework of the paper.**

## 2. METHODOLOGY

Two binary logit models with heterogeneity in means and variances were estimated. The first model investigated the likelihoods of switching to work-from-home during COVID-19 pandemic for people who did not previously work-from-home, and the second model estimated the probabilities of the willingness to continue work-from-home after COVID-19 for people who switched to work-from-home during COVID-19 pandemic.

To arrive at an estimable statistical model for the research questions, a function that determines the probability of either switching to work-from-home for respondents who did not previously work-from-home or the willingness to continue to work-from-home for respondents who started working from home during COVID-19 pandemic is defined as,

$$\mathrm{F}_n = \boldsymbol{\beta}\mathbf{X}_n + \varepsilon_n \tag{1}$$

where $\mathbf{X}_n$ is a vector of explanatory variables that affect the probability of observation *n* being a respondent who switched to work-from-home or is planning to work-from-home after the pandemic, $\boldsymbol{\beta}$ is a vector of estimable parameters, and $\varepsilon_n$ is a disturbance term. If the disturbance term is assumed to be generalized extreme-valued distributed, a binary logit model results as (McFadden, 1981),

$$\mathrm{P}_n(\mathrm{w}) = [1 + EXP\,(-\ \boldsymbol{\beta}\mathbf{X}_n)]^{-1} \tag{2}$$

where $\mathrm{P}_n(\mathrm{w})$ is the probability of the respondent *n* switching to work-from-home during COVID-19 pandemic when they did who did not previously work-from-home or probability of the willingness to work-from-home after COVID-19 pandemic if they worked from home during the pandemic.

To account for the possibility that one or more parameter estimates in the vector $\boldsymbol{\beta}$ may vary across respondents due to unobserved heterogeneity, a distribution of these parameters can be assumed, and Equation (2) can be rewritten as (see Washington et al., 2020)

$$\mathrm{P}_n(\mathrm{w}) = [1 + EXP\,(-\ \boldsymbol{\beta}\mathbf{X}_n)]^{-1}\, f(\boldsymbol{\beta}|\boldsymbol{\varphi})d\boldsymbol{\beta} \tag{3}$$

where $f(\boldsymbol{\beta}|\boldsymbol{\varphi})$is the density function of $\boldsymbol{\beta}, \boldsymbol{\varphi}$ is a vector of parameters describing the density function (mean and variance), and all other terms are as previously defined. With this definition random parameters logit model is defined (see Mannering et al., 2016, for a description of alternate methods of accounting for unobserved heterogeneity).

To account for the possibility of the mean and variance of individual parameters to be a function of explanatory variables where $\beta_n$ is defined as Equation 4, (Seraneeprakarn et al., 2017)

$$\beta_n = \beta + \boldsymbol{\theta}_n\mathbf{Z}_n + \boldsymbol{\sigma}_n EXP(\boldsymbol{\omega}_n\mathbf{W}_n)\,\boldsymbol{\varphi}_n \tag{4}$$

where $\beta$ is the mean parameter estimate, $\mathbf{Z}_n$ is a vector of explanatory variables that influence the mean of $\beta_n$, $\boldsymbol{\theta}_n$ is a vector of estimable parameters, $\mathbf{W}_n$ is a vector of explanatory variables that captures heterogeneity in the standard deviation $\boldsymbol{\sigma}_n$, $\boldsymbol{\omega}_n$is the corresponding parameter vector, and $\boldsymbol{\varphi}_n$ is a randomly distributed term that captures unobserved heterogeneity across respondents. Both models were undertaken by simulated maximum likelihood approaches using 1,000 Halton draws as they can deliver more efficient distribution of simulation draws than purely random draws (Bhat, 2003). Just like in other studies in travel behavior to achieve the most superior estimation, the normal distribution was assumed for random parameters (Barbour et al., 2020).

## 3. RESULTS AND DISCUSSION

Table 1 presents the results of binary random parameters logit model with heterogeneity in the means of random parameters on switching to work-from-home during COVID-19 pandemic for people who did not previously work-from-home, and Table 2 presents the results of a binary random parameters logit model with heterogeneity in the means of random parameters for continuing to work-from-home after the COVID-19 pandemic for people who started working from home during COVID-19 pandemic.

A total of 1,275 observations were used in estimating the first model (Table 1) and 367 observations (the 28.8 percent of the 1,275 people who were observed to switch to work-from-home during the pandemic) were used in estimating the second model (Table 2). Only variables that significantly improved the likelihood function at convergence (with over 90% confidence using a likelihood ratio test) were included in the model.

Starting with socio-demographic characteristics, it was found that age played a significant role in making shifts to work-from-home during the pandemic. Respondents who were above 50 years old and did not previously work-from-home were found to have a 0.004 lower probability of starting to work-from-home during the pandemic compared to their younger counterparts (Table 2). Once working from home during the pandemic, age had a more complex effect on the likelihood of continuing to work-from-home after the pandemic. For this, Table 2 shows that younger respondents (below 30 years old) were more likely to continue to work at home however this effect varied across the population of younger respondents (as indicated by the statistically significant random parameter).

For the probability of working from home during the pandemic, respondents who indicated having a graduate-level education had a higher likelihood of shifting to work-from-home during the pandemic (an average marginal effect of 0.027), but there was significant heterogeneity in this group as indicated by the statistically significant random parameter (Table 1). The variation across respondents for this education variable is also influenced by location with respondents living in large cities having a lower mean making them less likely to shift to work-to-home during the pandemic (Table 1).

Regarding continuing to work-from-home post-pandemic (Table 2), respondents who had a graduate education and switched to work-from-home during the pandemic had 0.047 lower probability to continue to work-from-home (Table 2).

As anticipated, household composition, and particularly the presence of children, played a role in COVID-19 related work-from-home probabilities. The estimation results in Table 1 show that the presence of children increased the likelihood of working from home during the pandemic (with an average net marginal effect of 0.020), but that there was significant heterogeneity in this effect across the population as indicated by the statistically significant random parameter. The mean of the random parameter was found to be influenced by college education (with college education increasing the mean) and by the male indicator (with men having a lower mean and thus decreasing the likelihood of working from home during the pandemic relative to females when children are present). The parameter indicating children present in the household was also significant in the probability of continuing to work-from-home after the pandemic (Table 2).

Respondents with low annual household income (below $25,000) who did not work-from-home before were found to have a significantly lower probability to begin work-from-home after the pandemic started (Table 1) as well as a higher probability to continue work-from-home.

As indicated by the marginal effects, respondents who indicated living in rural areas and large cities had varied response to the work-from-home paradigm.

Workers in the information technology sector, administrative/administrative, and business/financial who did not work-from-home before the pandemic were also found to behave differently depending on their employment sector.

**Table 1. Binary random parameters logit model with heterogeneity in the mean of random parameters on switching to work-from-home during COVID-19 pandemic for people who did not previously work-from-home.**

| Variable description | Parameter estimate* | t-Statistic | Marginal effects |
|---|---|---|---|
| Constant | 1.84 | 11.38 | |
| ***Socio-demographic characteristics and residential location*** | | | |
| Older respondents (1if respondent is above 50 years old, 0 otherwise) | -1.58 | -2.15 | -0.004 |
| Graduate education level (1 if respondent completed graduate education, 0 otherwise) (*Standard deviation of parameter distribution*) | 1.32 (*2.10*) | 2.48 (*1.42*) | 0.027 |
| Children present in household (1 if children are present in respondent's household, 0 otherwise) (*Standard deviation of parameter distribution*) | -3.68 (*4.32*) | -1.71 (*2.41*) | 0.020 |
| Low household income indicator (1 if annual household income is below $25k, 0 otherwise) | -1.42 | -3.14 | -0.007 |
| Rural area indicator (1 if respondent lives in rural area, 0 otherwise) | -1.21 | -2.38 | -0.006 |
| ***Job types and sectors*** | | | |
| Marketing (1 if respondent works in marketing/sales, 0 otherwise) | -2.25 | -1.86 | -0.002 |
| Information technologies (1 if respondent works in information technologies/technical service sector, 0 otherwise) | 0.99 | 3.20 | 0.017 |
| Administrative/administrative support (1 if respondent works in administrative/administrative support, 0 otherwise) | 1.13 | 3.29 | 0.012 |
| ***Heterogeneity in the mean of the random parameters*** | | | |
| Graduate education level: large city (1 if respondent lives in large city, 0 otherwise) | -1.37 | -1.99 | |
| Children present in household: college education (1 if respondent has a college education, 0 otherwise) | 3.06 | 1.98 | |
| Children present in household: male gender (1 if respondent is male, 0 otherwise) | -1.33 | -1.73 | |
| Number of observations | 1275 | | |
| Log likelihood at zero, LL(0) | -883.76 | | |
| Log likelihood at convergence, LL(β) | -520.13 | | |
| $\rho^2 = 1–LL(\beta)/LL(0)$ | 0.411 | | |

*Parameters defined for work-from-home

**Table 2. Binary random parameters logit model with heterogeneity in the mean of random parameters on continuing to work-from-home after COVID-19 pandemic for people who worked from home during COVID-19 pandemic.**

| Variable description | Parameter estimate | t-Statistic | Marginal effects |
|---|---|---|---|
| Constant | -0.75 | -2.49 | |
| ***Socio-demographic characteristics and residential location*** | | | |
| Young respondents (1if respondent is below 30 years old, 0 otherwise) (*Standard deviation of parameter distribution*) | -2.04 (*1.83*) | -2.75 (*1.44*) | 0.034 |
| Graduate education level (1 if respondent completed graduate education, 0 otherwise) | -0.77 | -2.35 | -0.047 |
| Children present in household (1 if children are present in respondent's household, 0 otherwise) | -0.96 | -2.65 | -0.070 |
| Low household income indicator (1 if annual household income is below $25k, 0 otherwise) | 2.36 | 2.68 | 0.017 |
| Small town indicator (1 if respondent is lives in small town, 0 otherwise) | -0.79 | -1.84 | -0.019 |
| Large city indicator (1 if respondent lives in large city, 0 otherwise) | 0.71 | 2.09 | 0.041 |
| ***Job types and sectors*** | | | |
| Information technologies (1 if respondent works in information technologies/technical service sector, 0 otherwise) | -0.64 | -1.85 | -0.028 |
| Administrative/administrative support (1 if respondent works in administrative/administrative support, 0 otherwise) | -0.70 | -1.53 | -0.014 |
| Business (1 if respondent works in business/financial sector, 0 otherwise) | -0.78 | -1.52 | -0.012 |
| ***Heterogeneity in the mean of the random parameters*** | | | |
| Young respondents: non-U.S. born respondent indicator (1 if respondent was not born in the U.S., 0 otherwise) | 3.12 | 1.97 | |
| Young respondents: children present in household (1 if children are present in respondent's household, 0 otherwise) | 1.57 | 2.40 | |
| Number of observations | 367 | | |
| Log likelihood at zero, LL(0) | -254.39 | | |
| Log likelihood at convergence, LL(β) | -216.02 | | |
| $\rho^2 = 1–LL(\beta)/LL(0)$ | 0.151 | | |

*Parameters defined for going to continue work-from-home

## 4. CONCLUSIONS

Two classes of variables were found significant: socio-demographic/residential location variables and job-sector variables. Each class delivered insights and allowed a better understanding of how different factors impacted work-related behaviors and teleworking. Although older respondents (above 50 years old) had a lower probability of starting to work-from-home during the pandemic, younger respondents (below 30 years old) exhibited a heterogeneous behavior when stating their willingness to continue work-from-home. This willingness was found to be impacted by their nationality (U.S. born individuals) and their household composition (children present). Respondents with a graduate education who did not work-from-home before the pandemic were found to have a heterogenous behavior that was impacted by living in a large city. Interestingly, while low-income respondents (under $25,000 annually per household) were likely to have a lower probability of starting to work-from-home, they were found to have a higher probability to continue to work-from-home after the pandemic (a finding revealed by the conditional nature of the results in Table 2 and the heterogeneity accounted for in the methodology). This finding could reflect an opportunity for lower-wage sectors to consider remote work for their employees. Lastly, a variable capturing children present in the household was found to be statistically significant in two models (Tables 1 and 2) and exhibited heterogeneous behavior across the population regarding the likelihoods of starting to work-from-home during the pandemic by producing statistically significant heterogeneity in the mean which was influenced by gender and education.

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